APPLICATION OF HYBRID-LEARNING NEURO-FUZZY GREY-BOX MODELS TO TEMPERATURE PREDICTION IN HOT ROLLING

José Ángel Barrios-Gómez, Gerardo Maximiliano-Méndez, Alberto Cavazos-González

Universidad Autónoma de Nuevo León (México)

DOI: http://dx.doi.org/10.6036/7859

The hot rolling process transforms steel slabs, with approximate dimensions of 10 m × 1 m × 0.2 m, into coiled sheets between 0.002 m and 0.0127 m thick and typically around 1 m wide. A hot rolling line consists of: 1) Reheating Furnace; 2) Roughing Mill (RM); 3) Finishing Mill (FM), consisting of 6 or 7 stands, 4) Cooling Tables; and 5) Down Coilers. The slab is reheated to approximately 1300 °C and then is transported to the RM where the initial thickness reduction takes place. The outcome of the RM is called transfer bar (TB) with typical dimensions of 90 m × 1 m × 0.0254 m. After the RM the TB is conveyed to the FM.

The FM has to be set up correctly to roll a specific product successfully. To achieve this goal, anticipated and accurate knowledge of the incoming bar temperature at the FM entry is crucial. However, the measurements at the FM entry are highly unreliable and hence the TB entry temperature has to be estimated from measurements at the RM exit, which are considerably more trustful.

Currently, in most rolling mills, the TB temperature estimation is performed by a physical model whose inputs are: 1) the RM exit temperature and 2) the TB traveling time from the RM exit to the FM entry.

Barrios *et al.* (2015) [1] presented several Grey-Box Models (GBMs) based on hybrid-learning (HL) neuro-fuzzy systems to estimate the TB temperature, owing to the adaptation capabilities of such systems [2-4]. The GBM inputs are the same as those of the physical model. The rolling line involved has two reversible RMs and a 6-stand FM. This technical report summarizes and discusses the results obtained in [1].

Parallel GBMs were used, in which the physical model and the fuzzy inference system (FIS) are interconnected such that they have common inputs while their outputs are added. The FIS prediction was interpreted as an additive term compensating the physical model prediction error. Four GBMs were developed each based on one of the following FISs: 1) 9-rule HL type-1 Mamdani, 2) 25-rule HL type-1 Mamdani, 3) 9-rule HL type-2 Mamdani and 4) 25-rule HL type-2 Mamdani. The membership functions (MFs) used were Gaussian functions. The systems were evaluated by 5 performance measures (PMs) applied on the prediction error as follows: 1) error mean value (ME), 2) error standard deviation (SD), 3) absolute mean error (MAE); 4) root mean square error (RMSE), and 5) the percentage of bars with an error within ±20°C, abbreviated as '% Bars ±20°C'. Their performance was compared with 20 fuzzy systems of different sorts developed in previous works [5-7].

Table 1 shows the main results. Some major findings are:

1. The top system is the **Mamdani type-1 HL 9-rule GBM** with **100%** of **'% Bars ±20°C'**, furthermore, it outperformed the rest of the systems in all the PMs used.
2. 18 out of 24 fuzzy-based systems outperformed the physical model.
3. The top 8 systems are GBMs; the top 6 systems include HL.
4. 9-rule GB models without HL are insufficient to model the TB temperature, showing large over-predictions with high dispersion.
5. HL-GB models performance is superior to that of the HL-FIS only systems.
6. Performance of **Mamdani type-1 9-rule GBM** improved considerably when HL is applied, **from 56.57% to 100%,** reducing both ME and SD.
7. HL or GBM improve performance considerably, used either together or separately.
8. The number of rules influences the system behavior depending on whether the system is a GBMs or an FIS only system. The 9-rule GBMs were occupying the bottom 3 positions moving upwards to the top 3 when HL was applied, while the 25-rule FIS only systems were the worst FIS only system becoming the best of their sort when HL was applied.

Publicaciones DYNA SL -- c) Mazarredo nº69 - 4º -- 48009-BILBAO (SPAIN)
Tel +34 944 237 566 – www.revistadyna.com - email: dyna@revistadyna.com

Some future activities are: to find the most suitable inference operations for temperature estimation, comparison of performance using different MFs and the test of higher order Sugeno FISs.

In some cases, a physical model is not available or may not be desirable, owing to its computational complexity since it is implemented by finite difference [8]. Therefore, the FIS only systems should be improved and further study is worthwhile. An improvement possibility would be as follows: the HL algorithm adapted some fuzzy sets of the FIS only systems discussed above such that their effects on the corresponding rule is almost insignificant (not shown here). This suggests that a rule-base extraction algorithm can bring some benefit to the FIS only system finding the optimal rule-base before applying HL. Other advantage of such algorithms is the incorporation of some extra inputs that influence the prediction without increasing the number of rules.

Table 1. Performance of some of the systems developed in [1, 5-7] ranked by "% Bars ±20°C".

Ranking	System	No. of Rules	SD	ME	MAE	RMSE	"% Bars ±20°C"
1	Type-1 Mamdani HL GB	9	**5.25**	**-0.17**	**4.16**	**5.25**	**100.00**
2	ANFIS GB	9	7.83	2.60	6.12	8.25	99.66
3	Type-2 Mamdani HL GB	9	5.45	2.98	4.67	6.21	99.51
4	Type-2 Mamdani HL GB	25	5.50	3.62	4.96	6.59	99.35
5	Type- 1 Mamdani HL GB	25	5.52	1.90	4.37	5.83	99.33
6	ANFIS GB	25	8.84	4.69	7.32	10.00	95.62
…	…	…	…	…	…	…	…
9	ANFIS FIS	25	15.54	-2.93	12.70	15.81	79.97
10	Type-2 Mamdani HL FIS	25	15.64	-1.81	12.72	15.74	79.27
11	Type 1 Mamdani HL FIS	25	15.69	-3.61	12.87	16.10	78.78
12	ANFIS FIS	9	15.50	2.09	12.93	15.64	78.51
13	Type-2 Mamdani HL FIS	9	15.66	-3.63	12.85	16.08	78.43
…	…	…	…	…	…	…	…
19	Physical Model	N/A	17.35	-6.14	14.44	18.40	73.97

This work was partially supported by PROMEP and CONACYT. We thank Dr. Luis Leduc, Dr. Jorge Ramírez, and Mr. César Villanueva from TERNIUM-Hylsa for the support provided and Dr. Oscar Castillo for providing the software to develop some of the type-2 fuzzy systems.

REFERENCES

[1] CAVAZOS-GONZALEZ, Alberto, BARRIOS-GOMEZ, Jose Angel, MAXIMILIANO-MENDEZ, Gerardo. ENTRY TEMPERATURE ESTIMATION IN A HOT STRIP MILL BY HYBRID-LEARNING TYPE-1 AND TYPE-2 FUZZY GREY-BOX MODELS . *DYNA New Technologies*, Enero 2016, vol. 2, no. 1, p.1-12. DOI: http://dx.doi.org/10.6036/NT7760

[2] Paliwal M, Kumar UA. "Neural networks and statistical techniques: A review of applications". *Expert Systems with Applications*. 2009. Vol.36-1 p. 2-17. (DOI:10.1016/j.eswa.2007.10005)

[3] Kar S, Das S, Ghosh PK. "Applications of neuro fuzzy systems: A brief review and future outline". *Applied Soft Computing*. 2014. Vol.15-2 p. 243-259. (DOI: http://dx.doi.org/10.1016/j.asoc.2013.10.014)

[4] Dareli T, Baycasoglu A, Altun K, et al. "Industrial applications of type-2 fuzzy sets and systems: A concise review". *Computers in Industry*. 2011. Vol.62-1 p.125-137. (DOI: http://dx.doi.org/10.1016/j.compind.2010.10.006)

[5] Mendez GM, Cavazos A, Soto R, et al. "Entry temperature prediction of a hot strip mill by a hybrid learning type-2 FIS". *Journal of Intelligent and Fuzzy Systems*. 2006, Vol.17-6 p.583-596.

[6] Barrios JA, Cavazos A, Leduc L, et al. "Fuzzy and Fuzzy Grey-Box Modelling for Entry Temperature Prediction in a Hot Strip Mill" *Materials and Manufacturing Processes*. 2011. Vol.26-1 p.66-77. (10.1080/10426910903124803)

[7] Barrios JA, Torres-Alvarado M, Cavazos A. "Neural and Fuzzy Grey-Box Modelling for Entry Temperature Prediction in a Hot Strip Mill". *Expert Systems with Applications*. 2012, Vol.39-1, p. 3374-3384. (DOI:10.1016/j.eswa.2011.09.025)

[8] Barrios JA, Torres-Alvarado M, Cavazos A, et al. "Neural and Neural Grey-Box Modelling for Entry Temperature Prediction in a Hot Strip Mill". *Journal of Materials Engineering and Performance*. 2011. Vol.20-7 p. 1128-1139. (DOI: http://dx.doi.org/10.1007/s11665-010-9759-1)

Publicaciones DYNA SL -- c) Mazarredo nº69 - 4º -- 48009-BILBAO (SPAIN)
Tel +34 944 237 566 – www.revistadyna.com - email: dyna@revistadyna.com